Does Urban Proximity Enhance Technical Efficiency in Agriculture? Evidence from China

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Abstract

We study whether rural areas close to urban centers enjoy a more productive agricultural sector than remote ones. We try to answer three questions: (1) Do rural areas close to urban centers and remote areas share the same agricultural technology? (2) Are rural areas close to urban center technically more efficient? (3) Do they enjoy a faster technical progress? The empirical examination is realized at the county level on a sample covering three provinces of the south-east of China from 2002 to 2007. Several interesting results are obtained. On the one hand, the type of agricultural technology adopted varies with the distance between the rural area and the urban center. On the other hand, urban proximity has a positive effect on agricultural productivity. Finally, our results confirm a previous finding : the most important component of total factor productivity growth in China is technical progress, whereas technical efficiency decreases it.

Keywords: Agricultural productivity, urban proximity, latent class stochastic frontier model, technical efficiency, technical change.

JEL Classification : O13, O18, Q10, R11

1 Introduction

Agricultural productivity growth in China represents a challenge in several ways. On the one hand, between 2001 and 2008, although population increased by 4% and per capita income doubled, cultivated area fell by nearly 6.5%. Therefore, given the increase in food demand and the growing shortage in arable land, agricultural productivity growth is the only solution to avoid importing large quantities of food. On the other hand, although non-agricultural activities represent a growing share of rural households' income, agriculture remains a major source of income for them. Thus, there is a need to raise agricultural productivity in order to reduce poverty and inequalities between rural and urban areas (Liu and Zhang, 2000). Finally, several studies insist on the positive impact of agriculture on the development of non-agricultural activities in rural areas (Haggblade *et al.*, 2002).

Thus, agricultural productivity is both important in terms of alimentary self-sufficiency, poverty reduction and economic development. That is the reason why many papers study the impact of different factors on agricultural productivity and efficiency in China. For instance, the effect of rural reforms (Fan, 1991; Lin, 1992; Brümmer *et al.*, 2006), migration (Taylor *et al.*, 2003), infrastructures (Fan and Zhang, 2004), land fragmentation (Chen *et al.*, 2009), environmental degradations (Rozelle *et al.*, 1997; Monchuck *et al.*, 2010), credit access, education and health (Liu and Zhang, 2000) have been estimated.

Although many determinants have been studied, very little attention was dedicated to the impact of urban proximity. However, for some authors, urban development would be the major solution to the low level of agricultural productivity (Nicholls, 1961). More precisely, agricultural productivity and rural development would be higher in rural areas close to urban agglomerations[1].

In terms of policy recommendations, it is important to study the impact of cities on rural areas[2] because it could influence the type of policies implemented. The idea is that before implementing a policy, one has to take into account the lack or existence of ties between the city and the rural areas. Where ties are strong, the optimal approach should be a global one, including at the same time rural and urban areas. On the contrary, where ties are weak, a more local policy, targeting only the rural area, would be preferable (Roberts, 2000). Moreover, the evidence of positive effects of cities on rural areas could contribute to reduce restrictions between urban and rural areas, such as the *hukou* or the lack of infrastructures, which are still very strong in China.

Very few articles studied the impact of urban centers on rural areas in China. In addition, there is no consensus on the effect of this variable. Fan *et al.* (2005) estimate that urban growth do not contribute to reduce rural poverty in China. Peng (1997) focuses on the impact of urban proximity

[1]"Urban-industrial hypothesis", Schultz (1951)

[2]In this article, rural areas refer to counties (*xiàn*) and urban areas to county-level cities (*xiànjishì*) or to urban districts (*shìxiaqu*) under prefectoral (*dìjíshì*) or provincial (*zhíxiáshì*) level cities.

on Township and Village Enterprises (TVE) development in rural areas. According to him, if cities often have a positive effect on TVE's development and success, the agricultural sector suffers from urban proximity. To our knowledge, only Benziger (1996) empirically analyzes the effect of urban proximity on agricultural productivity. The author concludes that in Hebei province urban proximity has a positive effect on agricultural productivity.

We contribute to the literature in several ways. Our first contribution is to propose a theoretical framework in which we highlight the different channels by which urban proximity can affect different components of agricultural productivity. Our second contribution is to analyse the effect of urban proximity on agricultural proximity more precisely. Indeed we consider the impact of the cities on two components of agricultural productivity : technical efficiency and technical change. Moreover, in order to estimate unbiased efficiency scores, we first check the validity of the homogeneous technology hypothesis. Thus we ask if (1) rural areas close to urban centers and remote rural areas have different technologies, (2) if rural areas close to urban centers are technically more efficient and (3) if they benefit from a higher rate of technical change. Our third contribution is to estimate a latent class stochastic frontier model (Greene, 2005) which, to our knowledge, has never been used to study technological heterogeneity in the Chinese agricultural sector. Actually, most studies on Chinese agriculture assume that technology is homogeneous. Only some studies consider heterogeneous technologies in China's agricultural sector (Mao and Koo, 1997; Cho *et al.*, 2008; Chen *et al.*, 2008; Chen and Song, 2008; Chen *et al.* 2009 and Ito, 2010). However, these authors use a two-step approach which leads to inefficient estimations unlike the latent class model (Orea and Kumbhakar, 2004). Finally, if some studies highlight that technological heterogeneity in the agricultural sector can arise from differences in geography and in the level of economic development (Chen and Song, 2008) or can exist according to the degree of intensification of agriculture (Alvarez and del Corral, 2010) or between organic and conventional agriculture (Mayen *et al.*, 2010), no one has studied if urban proximity can be a source of technological heterogeneity. Therefore our fourth contribution is to check if rural areas have different agricultural technologies according to their distance to urban agglomerations.

The remainder of this paper proceeds as follows. Section 2 is a theoretical analysis which identifies the main channels by which urban proximity can affect the type of technology, technical efficiency and technical change in the agricultural sector. Section 3 presents the data and section 4 the methodology. Econometric results are analyzed in section 5. Section 6 concludes and presents some policy recommendations.

2 Theoretical analysis

The literature dealing with the impact of urban proximity on agricultural technology and productivity is very sparce. In this theoretical analysis we try to disentangle the different channels by which urban proximity could affect agricultural technology, efficiency and innovation.

2.1 Urban proximity and agricultural technology

Most studies assume that agricultural production technology is homogeneous *i.e.*, that all units share the same production frontier[3]. However, if production heterogeneity is wrongly ignored, heterogeneity will be considered as inefficiency (Orea and Kumbhakar, 2004; Greene, 2005). Thus, to obtain unbiased efficiency scores, it is crucial to check this hypothesis. Moreover, if heterogeneity is wrongly ignored, unique and inefficient policy recommendations will be proposed (Bos *et al.*, 2010). That is why, several studies of Chinese agriculture have relaxed the homogeneous technology hypothesis. For example, Mao and Koo (1997) and Chen *et al.* (2008) conclude that, at the provincial level, different types of agricultural technology exist according to the different levels of economic development of the provinces. Other studies conclude that heterogeneous technologies can also arise from variations in geography or in factor endowments at the provincial level (Cho *et al.* (2007, 2008), Chen and Song (2008), Chen *et al.* (2009)). In this article, we investigate another source of technological heterogeneity : do differences in access to urban centers lead to different types of technology in the agricultural sector?

To our knowledge, no one has studied if heterogeneous technologies could exist between rural areas situated close to urban centers and remote rural areas. However, variations in the distance to urban centers lead to differences in factor endowments which could drive isolated rural areas and those closer to cities to develop different types of technologies[4]. Indeed, farmers in isolated rural areas often suffer from very poor access to modern inputs (fertilizers and machinery). Benziger (1996) estimates that in Hebei province, urban proximity positively affects the ratios of fertilizer and machine per hectare. Jacoby (2000) also observes that in Nepal, the quantity of fertilizer per hectare decreases when the travel time to the city rises. According to him, isolated farmers can adapt to their remoteness and develop other technologies substituting for example modern inputs by traditional inputs. As a consequence, Jacoby advises to reassess the technological homogeneity hypothesis for farmers close to cities and remote farmers. However, farmers in remote areas benefit from greater endowments in traditional inputs (land and labor). Indeed, rural areas close to urban centers suffer from losses in arable land which are

[3]A production frontier represents the maximum output that can be produced given the inputs and the technology.

[4]From an empirical point of view, this spatial heterogeneity drives the production frontier coefficients to vary across rural areas, according to their distance to the city

converted for urban uses. For example, in Beijing, Tianjin and Hebei's region, urban area rose by 71% between 1990 and 2000. And, among the new areas converted for urban uses, 74% were farmlands (Tan *et al.*, 2005). As a result, the closer the rural area is to an urban agglomeration, the scarcer the arable land is. Moreover, if rural areas close to urban centers are less endowed with arable lands, they are also less endowed with labor. Indeed, urban proximity makes migration easier and increases the number of job opportunities outside agriculture. Indeed, workers in rural areas close to cities benefit both from job opportunities in TVE which are concentrated around cities (Peng, 1997) and from job opportunities directly in cities (according to Gale *et al.* (2002), nearly 40% of rural workers who are employed in the non-agricultural sector are working in urban areas). This contributes to reduce the surplus of agricultural labor in rural areas close to urban centers[5]. To summarize, we expect that factor endowments vary across rural areas according to their distance to urban centers. As a consequence farmers, facing differences in factor endowments according to their distance to urban centers, will most likely develop different types of technologies.

2.2 Urban proximity and technical efficiency[6]

In terms of policy recommendations, it is important to study technical efficiency because it does not make sense to adopt new technologies if one cannot manage to efficiently use existing ones (Kalirajan *et al.*, 1996). Several studies estimate that Chinese agriculture suffers from a degradation in its level of technical efficiency (Kalirajan *et al.*, 1996; Mao and Koo, 1997; Chen *et al.*, 2008). Therefore, it is particularly important to examine its determinants. To our knowledge, no article has studied the impact of urban proximity on technical efficiency in the Chinese agricultural sector. However, the city can affect the level of technical effiency of its neighbouring rural areas in several ways : by stimulating workers to intensify their labor effort; by facilitating the diffusion of knowledge and by diversifying the farmers' activities. A priori, the effect of urban proximity on agricultural efficiency is ambiguous.

First of all, the city offers opportunities to become rich and thus, encourages farmers to provide more labor effort. Since the beginning of transition, agricultural reforms have been implemented. They give the opportunity for farmers to become rich and reward individual efforts. Several studies conclude that agricultural reforms increase productivity in the Chinese agricultural sector : the introduction of the "household responsibility system" and the price reform lead to important productivity gains (Fan,

[5]We can also observe a better adjustment of the labor supply in rural areas close to urban centers in other countries such as the United States (Partridge and Rickman, 2008) where there is no institutional constraint on migration as in China (*hukou*).

[6]Technical efficiency measures the ability of a county to produce the maximum output it can produce given the inputs and the technology. A rural area is considered as technically inefficient if its effective production level is lower than the maximum production level.

1991; Lin, 1992). Yet, as Benziger (1996) underlines, market access determines if farmers can enjoy these enrichment opportunities or not. Indeed, the urban market gives the farmers the opportunity to sell their production, which encourages them to give up self consumption agriculture in favor of market agriculture. Moreover, these farmers also enjoy lower transport costs and thus, higher sale prices for their products. As a consequence, as they are given the possibility to become rich, farmers close to cities are encouraged to increase their agricultural production, to diversify and to be more efficient.

Secondly, cities are information centers where new ideas emerge. Rural areas close to cities benefit from the diffusion of knowledge and ideas which enables them to better control their environment and new technologies *i.e.* to be more efficient (Jacobs, 1969).

Nevertheless, urban proximity could also deteriorate the level of agricultural technical efficiency in neighbouring rural areas, diversifying agricultural workers' activities. As we said in section 2.1, non-agricultural job opportunities are more numerous in rural areas close to cities. Because of this, individuals are encouraged to share their labor time between agricultural and non-agricultural activities. Thus in 1995, one third of rural workers in China already worked both in the agricultural sector and in the non-agricultural sector (Knight and Song, 2003). Several studies investigate if the diversification of farmers' activities reduced the level of technical efficiency in the agricultural sector. Individuals have indeed less time to allocate to agriculture and may abandon time intensive activities such as the research of better practices or of better management. Goodwin and Mishra (2004) estimate that in the United States more time dedicated to non-agricultural activities leads to a weaker level of technical efficiency in the agricultural sector.

2.3 Urban proximity and technical change[7]

Technical progress could be the most important component of agricultural productivity in China (Mao and Koo, 1997; Chen *et al.*, 2008). Moreover, Ma *et al.* (2007) estimate that in the Chinese dairy sector, suburban farms benefit from a higher rate of technical progress than farms in the dairy sector as a whole. Indeed, as we will see in this section, a city can stimulate the technical progress of its neighbouring rural areas in several ways : making the adoption of new technologies (1) possible, (2) profitable and (3) "compulsory". However, the seizure of farmland, more likely to happen in rural areas close to urban centers, could also discourage innovation.

Firstly, urban proximity makes technical change possible. On the one hand, it gives access to new technologies which can be difficult to obtain in rural markets. Huang and Rozelle (1996) estimate that, in the rice sector in China the adoption of new technologies not only depends on the producer's choice,

[7]Technical change measures the shift of the frontier over time. In the case of technical progress, for a given quantity of inputs, it is possible to produce more output.

but also on the possibility to obtain it. On the other hand, in the context of imperfect insurance and capitals markets, urban proximity gives the farmers the means to finance their investments. Indeed, farmers who enjoy access to the urban market can sell their production there and thus obtain liquid assets, whereas farmers in remote areas suffer from liquidity constraints which prevent them from investing (Smith *et al.*, 1994). Moreover, non-agricultural job opportunities are more numerous in rural areas close to urban centers which contributes to the diversification of rural households' incomes. Thus, this gives them an insurance against agricultural risks which stimulates innovation.

Secondly, urban proximity turns investment in new technologies into a profitable option. Indeed, farmers near urban centers enjoy both more important market opportunities and a higher sale price for their production compared with farmers in remote areas. Hence, urban proximity makes investment in new technologies not only possible but also profitable, a fact which stimulates technical progress (Tauriainen and Young, 1976). On the contrary, in remote areas where there exists very few possibilities to grow rich, investment is not rewarded and therefore, technical progress would be slower.

Thirdly, urban proximity makes technical change "compulsory". Indeed, in peri-urban areas, the competition between the different uses of land (housing, urban infrastructures, industrial, commercial or agricultural activities) is stronger than in remote rural areas. According to Livanis *et al.* (2006), in peri-urban areas, the only lands which will not be converted for urban uses are lands dedicated to high yield cultivation. In this way, proximity stimulates the adoption of new technologies. In addition, the scarcity of factors also encourages innovation. The idea is that the more a factor becomes scarce, the more its price increases. Thus, the aim of technical progress is to use the factor, which is becoming scarce, less (Binswanger, 1986)[8]. As we said in section 2.1, urban proximity increases farmland scarcity. Therefore, although China as a whole is poorly endowed with arable lands, we can expect that land scarcity will be more marked in rural areas close to cities. That is the reason why, these rural areas would adopt new technologies faster. However, if land scarcity has an initial positive impact on technical change, beyond a certain level, land scarcity may go against the adoption of new agricultural technologies. This can be the case for farms located in areas where land scarcity is so important that it is impossible to increase the size of the farm. In this case, investment in non-agricultural activities can seem more profitable and be made at the expense of investment in the agricultural sector (Goldman and Smith, 1995).

If the previous arguments underline that urban proximity stimulates investment because it makes it possible, profitable and compulsory, urban proximity can also discourage innovation. The lack of respect

[8]The adoption and orientation of new technologies in agriculture is influenced by factor endowments. Countries with different factor endowments will not have the same type of technology. In a country like China where land scarcity is a major issue, technical progress consists in adopting technology which maximizes land yields through the adoption of biological and chemical technologies. On the contrary, in the United States where land is abundant but labor is scarce, technical progress consists in investing in mechanical technologies.

for leases of farmland could discourage innovation in rural areas close to cities. Actually, farmers have leases which give them the right to use their land but the land ownership remains collective. Although the duration of the lease has been increased these last years, reaching 50 years today, some farmers still suffer from relocation. Since land ownership is collective, the local authorities decide what to do with the land although farmland is under lease. Thus, sometimes, local authorities relocate farmers in order to obtain their farmland to turn it over to non-agricultural uses which are more lucrative (Naughton, 2007). As non-agricultural uses are more numerous in areas close to cities, farmers have more chance of being relocated in rural areas close to cities. We can expect this to slow down investment and discourage farmers from managing their farmland in a sustainable way in rural areas close to urban centers.

All the transmission channels through which cities can affect agricultural technical efficiency and technical change in neighbouring rural areas are summarized in the following table.

Table 1: Effect of urban proximity on agricultural technical efficiency and technical progress

Transmission channels	**Expected effect**
Technical efficiency :	
1. Opportunity to become rich : incentive to intensify labor effort	+
2. Knowledge diffusion : better control on the environment	+
3. Diversification of workers' activities	-
Technical progress :	
1. Possibility of technical change	
i. Better access to new technologies	+
ii. Soften liquidity constraints	+
iii. Provision of an insurance	+
2. Profitability of technical change	+
3. Necessity of technical change	
i. Competition for the use of land	+
ii. Land scarcity	+ then -
4. Uncertainty of land ownership	-

3 Data

Following Benziger (1996) and Peng (1997), we use county-level data to study the effect of cities on rural areas in China. Our sample consists of 117 counties belonging to three provinces of the south-east of China : Anhui, Zhejiang, and Jiangsu, over the period 2002-2007. The limited availability of indicators at the county level lead us to study these three provinces which have published the necessary indicators over quite a long period. The dataset on rural counties is from various issues of the Provincial Yearbooks of Anhui, Zhejiang and Jiangsu and from the China Statistical Yearbook for Regional Economy (2003). The definitions and descriptive statistics of the variables used are provided in Tables A.1. and A.2. in the appendix. One advantage of this period of time is that very few administrative changes occured, which enables us to avoid suffering from "reclassification bias" unlike former studies[9] (Benziger, 1996; Gu *et al.*, 2001 for example). In addition, one advantage of working on these three provinces is that they share similar characteristics in terms of geography and cultural conditions (Fan, 1991). Indeed, studies which assume that regional technological heterogeneity exists in China bring together these three provinces in a homogeneous group (Cho *et al.*, 2008; Chen *et al.* 2009). Thus, we will check if technological heterogeneity exists between the counties of these three provinces which are generally considered as sharing the same production technology. Moreover, relating to urbanization, Jiangsu and Zhejiang are to a large extent above the national average with urbanization rates of 53.2% and 57.2% respectively compared with 44.94% for China as a whole in 2007. These two coastal provinces are very urbanized; their study enables us to take into account negative externalities arising from an intense urban concentration. On the contrary, in Anhui province, the urbanization rate only reached 38.7% in 2007 and some rural counties still remain remote. Therefore, our sample is composed of rural counties sufficiently heterogeneous in terms of proximity-remoteness to the cities to carry out our study.

To carry out the study, we create two indicators of urban proximity. We assume that the closer the city is to the rural area, the higher the effect of the city on the rural area will be. Moreover, the bigger the city, the higher the effect will be. We measure the city size in two different ways : by the GDP and by the population of the city. To take into account these two dimensions (distance and size), we use

[9] The more dynamic rural areas were precisely those which enjoyed a change in administrative status; most of them became a county level city (Chan *et al.*, 2008). According to the data on the administrative divisions of these three provinces (See table A.3. in appendix and the China Statistical Yearbooks from 2003 to 2008), Anhui did not experience any administrative change between 2002 and 2007. We count two administrative changes in Jiangsu province : Yandu county became a district of Yancheng city and Suyu a district of Suqian city between 2003 and 2004. As for Zhejiang, two districts appeared during our sample period but the number of rural counties remains stable; thus, these new districts probably arose from the transformation of a share of a rural county into an urban district. Few administrative changes occured between 2002 and 2007 in the provinces studied. As a consequence, it should not be a source of bias in our study.

the spatial econometrics tools. We create two exogenous spatial lag variables:

$$WGDP_{it} = \sum_j w_{ij} \cdot GDP_{jt} \ , \ \textit{with } w_{ij} \textit{ the spatial weights matrix and GDP the GDP in city } j$$

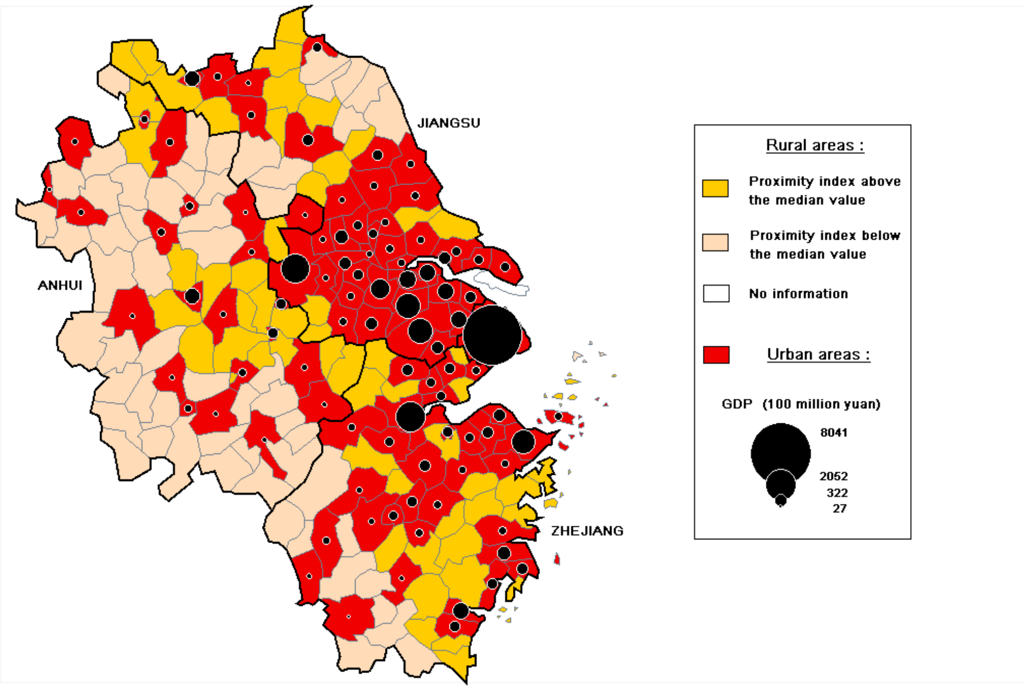
$$WPOP_{it} = \sum_j w_{ij} \cdot POP_{jt} \ , \ \textit{with } w_{ij} \textit{ the spatial weights matrix and POP the population in city } j$$

The variable of proximity is therefore an interactive term between the city size (population or wealth) and the inverse of the distance between the city j and the rural area i (w_{ij}). Distance is calculated using latitude and longitude of each county and city[10]. Cities are either cities at the county level or the urban districts under cities at the prefectoral and provincial levels. Following Soule *et al.* (2000), we consider that all the cities situated within fifty miles can affect counties even if they are not located in the same province as the county. The following map represents the level of urban proximity for each rural county of our sample[11]. To make the representation easier, we arbitrarily distinguish on the map two categories of counties: those for which the urban proximity level is lower than the median value and the ones for which the value is higher. It appears clearly that the counties for which urban proximity is high are the counties close to the big cities. For ease of representation, cities of the surrounding provinces (Shandong, Henan, Hubei, Jiangxi and Fujian) do not appear on the map. However, they are taken into account in the calculation of the proximity indicators when they are located less than 50 miles from a rural county.

[10]Data available on the U.S. Geological Survey web site : http://www.usgs.gov/. Data on the GDP and the population of the cities are from various issues of the China City Statistical Yearbooks.

[11]Urban proximity is calculated taking the GDP of the cities. Another map representing the distribution of urban proximity calculated using the city population is available; See Figure A.1. in appendix.

Figure 1: Urban proximity ($WGDP$)



4 Methodology

We shall try to answer the following three questions : (1) Do rural areas close to urban centers and remote rural areas have different technologies? (2) Are rural areas close to cities more efficient? (3) Do they enjoy faster technical progress? To answer these questions, we proceed in three steps. First, we estimate a latent class stochastic frontier model in order to test if technological heterogeneity exists between rural areas and to study if this heterogeneity is determined by the distance between the rural area and the city. This first step enables us to identify different groups of rural areas. Secondly, we calculate technical efficiency scores to compare the average levels of efficiency between the two groups identified. Thirdly, we decompose total factor productivity (TFP) growth for each group into several components.

4.1 Latent class frontier model

To test if there is technological heterogeneity, we estimate a latent class frontier model (Greene, 2002, 2005; Orea and Kumbhakar, 2004). The model divides the sample into different classes (groups) according to the type of agricultural technology. The technology of rural areas belonging to the same class is homogeneous and is represented by a unique frontier. On the contrary, the technology of rural areas belonging to different classes is heterogeneous and is represented by different frontiers. In other words, the coefficients of the production frontier vary across the groups. In addition, this model estimates the probability for each rural area to belong to each class. Then, for each rural area, we consider as the reference frontier, the frontier with the highest probability to represent its production process[12].

Several methodologies have been used to take into account the technological heterogeneity. Here, a latent class frontier model is estimated because it offers several important advantages. On the one hand, the latent class model divides the sample into different groups and estimates the parameters of the production frontier in one step which allows us to obtain efficient estimations contrary to the two step approaches[13] (Orea and Kumbhakar, 2004). On the other hand, the model determines if the separating variables (variables affecting the probability of belonging to the different classes) are pertinent. In other words, it enables us to test if urban proximity influences the type of production technology. Finally, statistical criteria enable us to choose the number of classes (i.e., the number of existing technologies).

The stochastic approach forces us to choose a specification for the production frontier. Although it imposes restriction on the technology, we estimate a Cobb-Douglas function which does not suffer from multicolinearity problems contrary to flexible functional forms (Hassine and Kandil, 2009 and Mayen *et al.*, 2010). The following latent class stochastic frontier model is estimated by the maximum simulated likelihood (Greene, 2003) using Limdep 9.0 :

$$\ln(y_{it}) = \alpha|_j + \sum_{k=1}^{5} \beta_k|_j \cdot \ln(x_{kit}) + \varphi|_j \cdot Trend + \sum_{p=1}^{2} \phi_p|_j \cdot Dloc_p + \delta|_j \cdot Disl + v_{it}|_j - u_{it}|_j \qquad (1)$$

where j refers to the class, i to the county, p to the province, k to the input and t to the year. The error term v_{it} is a symetric error component, assumed to be iid and to follow a normal distribution centered at zero. It is also assumed to be independent of the inefficiency term u_{it}. The one-sided error component, u_{it}, is assumed to follow a gamma distribution which is more flexible than the half-normal or exponential model as it does not impose the restriction that most firms are fully efficient.

In the model estimated, we identify two different categories of variables : the production frontier variables and the separating variables. First, with regard to the production frontier variables, the

[12] A detailed description of the latent class frontier model can be found in Greene (2005) and in Orea and Kumbhakar (2004).

[13] Two step approaches first divide a priori the sample into several groups according to a variable considered as pertinent. Then, a stochastic frontier model is estimated for each group separately. See Mao and Koo (1997), Chen *et al.* (2008), Chen and Song (2008) and Mayen *et al.* (2010). Contrary to these two-step approaches, the latent class model classifies the sample in different groups endogenously and uses the information of one class to estimate the technology of the other class.

dependent variable and the inputs (x_{it}) are the variables currently introduced in the literature on agricultural productivity. We use the logarithm of the gross output value of farming in constant prices as dependent variable. We consider two traditional inputs (labor and land) and two modern inputs (chemical fertilizers and machinery)[14]. We also introduce a time trend ($Trend$) to account for technical change. Provincial fixed-effects ($Dloc$) and a dummy equal to one if the county is an island ($Disl$) are introduced in order to control for agro-climatic conditions (Alvarez and del Corral, 2010; Mayen *et al.*, 2010).

Secondly, the variable of interest "*proximity*" is introduced among the separating variables (we take the average by county over the period as it is in the literature). We introduce each indicator of proximity, one after the other, as separating variables in order to see if each measure of proximity affects the class membership probability. In addition to the proximity indicator, we introduce provincial fixed-effects and the dummy for islands as separating variables because regional physical differences could affect technology (Alvarez and del Corral, 2010).

4.2 Calculation of technical efficiency scores

Once the latent class frontier model has been estimated, it is possible to calculate the individual technical efficiency scores. These scores are obtained by comparing a rural area's effective level of production to the maximum output it could produce *i.e.* to its production frontier. In the case of a stochastic frontier model with homogeneous technology, efficiency scores are calculated with a unique method as all the rural areas share the same production frontier. However, two methods can be used in the case of the latent class model as each rural area is associated, with a certain probability, with several frontiers. A first method consists in comparing each rural area to its most likely production frontier (the frontier to which it has the highest probability of belonging to). In this case, each county is associated with one frontier and the individual efficiency scores are obtained using the following formula:

$$TE_{it} = exp(-\hat{u}_{it}) \tag{2}$$

The second method consists in calculating the weighted average of efficiency scores obtained with the different frontiers, using the probabilities as weights. In this case, each county is associated with several frontiers and the individual efficiency scores are obtained with the following formula :

$$TE_{it} = \sum_{j=1}^{J} P(i/j) \cdot exp(-\hat{u}_{it}|_j) = \sum_{j=1}^{J} P(i/j) \cdot TE_{it}|_j (3)$$

[14] Although it is important to introduce indicators of input quality (Craig *et al.*, 1997), we do not introduce any variable to control for quality because we do not have such data.

where P(i/j) is the probability for county i to belong to class j. We calculate the technical efficiency indexes with the second method which gives, according to us, the more precise efficiency scores.

4.3 Decomposition of total factor productivity growth

In order to identify which factors contribute to the TFP growth of each identified group, we undertake a decomposition of TFP growth. More precisely, we decompose the index of TFP growth into three components : technical change, technical efficiency change and scale change (Kumbhakar *et al.*, 2000) :

$$P\dot{T}F_{it|_j} = TC + TEC + SC = \frac{\partial \ln f|_j}{\partial t} + \frac{-\partial u_{it|j}}{\partial t} + \frac{\varepsilon|_j - 1}{\varepsilon|_j} \sum_{k=1}^{5} \varepsilon_k|_j \frac{\partial \ln x_{it}}{\partial t} \tag{4}$$

where $\varepsilon|_j$ is the scale elasticity for class j and $\varepsilon_k|_j$ is the elasticity of output with respect to input k for class j. This decomposition enables us to study if the components of PTF growth differ between groups.

5 Results

5.1 Homogeneous or heterogeneous technology?

The first step consists in checking if the production technology in our sample is homogeneous or not. We follow the procedure employed in the literature : we estimate latent class frontier model with different numbers of classes and we compare the value of the information criteria obtained for each specification. We use the Akaike (AIC), Bayesian (SBIC) and Hannan-Quinn (HQIC) information criteria[15]. The preferred specification is the one with the lowest value of the information criteria. According to the criteria, the preferred specification is the one with two groups : we reject the technological homogeneity hypothesis (See Table A.4. in the appendix).

The following table presents the latent class frontier estimation results. The first part of the table gives the production frontier parameters, the second part the inefficiency parameters and the third part the separating variables parameters.

We investigate now the determinants of technological heterogeneity. More precisely, do the two groups identified differ in terms of urban proximity? To answer that, we check if the indicators of proximity significantly affect the membership probability. We conclude that rural areas close to urban

[15] These information criteria can be written as : $AIC(J) = -2\ln LF(J) + 2 \cdot K$; $SBIC(J) = -2\ln LF(J) + K \cdot \ln n$; $HQIC(J) = -2\ln LF(J) + c \cdot \ln(\ln n)$, where k is the number of parameters to be estimated, n the number of observations and LF(J) the value of the likelihood function for J classes.

Table 2: Estimation of the latent class model

	Class 1 : counties close to urban centers		**Class 2 : remote counties**	
	Estimates	S.E.	Estimates	S.E.
Frontier				
Constant	2.415***	0.026	1.946***	0.038
Land	0.280***	0.018	0.222***	0.030
Labor	0.195***	0.020	0.246***	0.016
Machinery	0.156***	0.017	0.117***	0.016
Fertilizer	0.228***	0.014	0.287***	0.022
Trend	0.059***	0.005	0.046***	0.006
Jiangsu	0.013	0.026	0.318***	0.046
Anhui	-0.347***	0.027	-0.037	0.035
Island	-0.694***	0.035	-1.269***	0.065
Efficiency parameters				
Sigma	0.190***	0.014	0.328***	0.014
Lambda	1.833***	0.525	3.285***	0.674
Regime membership probability parameters				
Constant	-1.665***	0.633	Reference group	
Jiangsu	1.39**	0.638	Reference group	
Anhui	1.479***	0.554	Reference group	
Island	1.377	1.851	Reference group	
Proximity pop	0.064*	0.038	Reference group	
Proximity gdp	0.025**	0.013	Reference group	
Observations	348		354	

Note : *, **, *** indicate significance at the 10%, 5% and 1% levels respectively. The log-likelihood value is 198.55. The indicators of proximity are included one after the other.

centers have significantly more probability of belonging to class 1 compared to class 2[16]. We also carry out a test of difference between means to make sure that the two groups differ in terms of proximity. The t-test of difference between means confirms that urban proximity is significantly higher in class 1 than in class 2 (See table 5.b. in the appendix). As a consequence, we identify two kinds of technology : the technology of rural areas close to urban agglomerations (class 1) and the technology of remote rural areas (class 2). A first important result is that agricultural technology differs according to the distance between the rural area and the city.

When it comes to the estimated parameters for the production frontier, several interesting results are obtained. On the one hand, in both groups, output depends more on fertilizers (biological technologies) than on machinery which is consistent. Indeed, biological technologies (or land-saving technologies) should be more important than mechanical technologies (or labor-saving technologies) in China, where land is scarce and agricultural labor abundant. On the other hand, both groups experience decreasing returns to scale (egual to 0.86 and 0.87 for the first and the second group respectively). These values are very similar to those obtained by Chen *et al.* (2009) and Cho *et al.* (2007) who estimate, respectively, returns to scale in East China to be 0.88 and 0.85. Finally, rural areas close to urban centers enjoy faster technical progress compared to remote areas (5.9% against 4.6% per year) which confirms our expectations and constitutes our second important result : urban proximity stimulates the accumulation of new technologies in the agricultural sector. The rates of technical change obtained are high but it is not surprising considering that the sample is composed of Jiangsu, Zhejiang and Anhui provinces. Besides, according to the calculations by Chen *et al.* (2008), Jiangsu and Zhejiang are just after Shanghai in terms of agricultural technical progress.

5.2 Technical efficiency scores

If urban proximity stimulates technical change, does it also enhance technical efficiency? In the second part of Table 2, both of the inefficiency parameters, *lambda*[17] and *sigma*[18], are significant. This means that, in both groups, the effective level of production of the counties is lower than the maximum output they could produce because most of them are technically inefficient. More precisely, the difference between the effective level of production and the frontier is almost entirely due to inefficiency (u) and not to noise (v). In order to check if one group is more efficient than the other group, we calculate technical efficiency scores for each county at each period of time. The average efficiency scores for the

[16]The class membership probability is calculated with a multinomial logit model; therefore, the probability of belonging to class 1 is relative to a reference class, here, class 2.

[17]*Lambda* corresponds to the standard deviation of inefficiency divided by the standard deviation of the noise term : $\lambda = \frac{\sigma_u}{\sigma_v}$.

[18]*Sigma* corresponds to the composite standard deviation : $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$.

two groups are presented in table 3.

Table 3: Average technical efficiency indexes by class

Counties close to urban centers	Remote counties
0.878	0.790
(0.038)	(0.104)

Note : standard deviations in parenthesis

The third important result of this study is that rural areas close to cities are technicaly more efficient than remote rural areas. According to the Wilcoxon test[19], this difference is statistically significant at the 1% level. This result is contrary to the conclusion of Nehring *et al.* (2006) according to which urban proximity negatively affects farmers' technical efficiency level. However, their study is carried out on a sample of farmers in the Corn Belt, the production context of which is very different from the Chinese one. Therefore, we do not expect urban proximity to impact technical efficiency by the same transmission channels. For example, if urban proximity most likely enhances efficiency in China giving farmers more opportunity to become rich, in the Corn Belt, this transmission channel should not be at work as even farmers in the most remote areas have the opportunity to become rich. One possible shortcoming of this study however, is that we assume that remote counties and counties close to cities produce the same agricultural products, which could be misleading. Indeed, we conclude that counties close to cities are more efficient than remote ones thanks to their urban market access which gives them incentives to produce efficiently. Nevertheless, their higher level of efficiency could also arise from the fact that the agricultural output they produce is less complicated to yield than those of the remote counties. To relax the assumption according to which all the counties produce the same type of agricultural output, we could estimate a production frontier either with several outputs or with only one type of output (grain or vegetables for example). Yet, the lack of disaggregated output data at the county-level prevents us from estimating these models. An other objection could be made regarding the direction of causality. It could indeed be argued indeed that the most enterprising farmers settle close to cities in order to benefit from the urban market. In this case, the faster rate of technical change and the higher level of technical efficiency would not stem from urban proximity but from the differences in farmers characteristics. However, in China, it is very likely that the causality runs from urban proximity to agricultural productivity. Indeed, farmlands are allocated to farmers by the autorities and nothing indicates that the most enterprising farmers are given the land close to urban centers. In other words,

[19]To test the difference between means for efficiency scores, we use the non parametric Wilcoxon test as efficiency scores do not follow a normal distribution. See table A.6. in appendix.

the location of Chinese farmers should be exogeneous to their ability to produce.

5.3 Decomposition of total factor productivity growth

A decomposition of total factor productivity growth is undertaken in order to study how technical change, efficiency change and scale change contribute to TFP growth for each group. The decomposition results are presented in table 4.

Table 4: Components of total factor productivity growth

	Counties near to urban centers				Remote counties			
	EC	**TC**	**SC**	**TFP**	**EC**	**TC**	**SC**	**TFP**
2002-2003	-0.069	0.059	0.011	0.001	-0.107	0.046	0.006	-0.055
2003-2004	0.090	0.059	-0.025	0.125	0.130	0.046	-0.021	0.155
2004-2005	-0.031	0.059	-0.015	0.013	-0.035	0.046	-0.008	0.003
2005-2006	0.019	0.059	0.001	0.079	0.034	0.046	0.001	0.081
2006-2007	-0.036	0.059	0.020	0.043	-0.039	0.046	0.008	0.015
mean	-0.005	0.059	-0.002	0.052	-0.003	0.046	-0.003	0.040

Note : EC, TC, SC, TFP indicate respectively Efficiency Change, Technical Change, Scale Change and Change in Total Factor Productivity; technical change is constant over the sample period (it follows a linear trend).

On the one hand, both groups benefit from a TFP growth between 2002 and 2007. On average, the rate of TFP growth is estimated to be 5.2% and 4% per year in rural areas close to urban centers and in remote rural areas respectively. These rates of TFP growth are high but again, this is not surprising given our sample. Indeed, according to Chen *et al.* (2008), Jiangsu and Zhejiang's TFP growth rates in the agricultural sector are largely above the national average (estimated to be 4.2% and 7.3% per year respectively over the period 1999-2003 compared to 2.5% for China as a whole). On the other hand, rural areas close to cities benefit from faster TFP growth mainly thanks to their faster rate of technical progress.

Regarding the components of TFP change, for the two groups, technical change is the component which contributes the most to TFP change, followed by efficiency change. Scale change contributes very little to TFP change. In both groups technical change contributes heavily and positively to TFP growth. However, the decline in technical efficiency negatively impacts TFP growth which confirms an existing finding in the litterature (Kalirajan *et al.* (1996), Ma *et al.* (2007), Chen *et al.* (2008)). Technical inefficiency seems to be the weakness of the Chinese agricultural sector both in terms of level and of evolution. Indeed, in the Chinese agricultural sector, farmers produce less output than the maximum output they could produce. But, what is even more worrying is that since 2002, Chinese counties have been moving away from their production frontier i.e., the gap between their effective level of production and the maximum output they could produce has been widening. However, although technical efficiency negatively affects TFP growth, technical progress is so high that it leads to a strong TFP growth rate over the period. The observation of a high rate of technical change coupled with a deterioration in the technical efficiency level is nothing new in the literature. Indeed, fast technical progress could coincide with a deterioration in technical efficiency if farmers do not have the time to assimilate new technologies (Mao and Koo, 1997). Besides, as counties close to cities benefit from a higher rate of technical progress, it could explain why these counties also suffer from a slightly higher deterioration in technical efficiency (-0.5% per year against -0.3% for remote counties in average).

6 Conclusion

In this paper, we answer three questions : (1) does urban proximity affect the type of agricultural technology of its neighbouring rural areas? (2) Does it affect their technical efficiency level? (3) Does it affect their rate of technical change? To answer them, we proceed in three steps. Firstly, we estimate a latent class stochastic frontier model to test whether Chinese rural areas are technologically heterogeneous and to determine if urban proximity influences the type of technology adopted. Then, we identify two groups of rural areas whose technology is different : remote counties and counties near cities. Secondly, we calculate efficiency scores and thirdly we decompose the TFP growth of each group into different components.

Several interesting results are obtained. On the one hand, urban proximity does affect the type of agricultural technology. On the other hand, it would appear that urban proximity enhances agricultural productivity. Indeed, rural areas close to cities are technically more efficient. Moreover, they enjoy faster TFP growth which can be explained by the fact that they benefit from a higher rate of technical change. Lastly, the results confirm an existing finding : the most important component of TFP growth in the Chinese agricultural sector is technical change whereas technical efficiency change decreases it.

Several policy recommendations can be proposed. First, as technological heterogeneity exists, it is necessary to implement local policies, taking into account the relative remoteness of rural areas. Secondly, it seems that urban proximity enhances agricultural productivity; therefore, it would be of real benefit to strengthen the ties between rural and urban areas. Thirdly, in order to continue to increase TFP in the agricultural sector, efforts have to be concentrated on technical efficiency. Different solutions can be considered according to the distance between the rural areas and the cities. Remote rural areas, in which the technical efficiency level is low (0.79 over the period), could experience strong

TFP growth if they reduced their technical inefficiency level. The low level of technical efficiency in these areas probably arises from the lack of incentive of farmers : they have few opportunities because of their poor access to urban markets. Strengthening ties between rural and urban areas would increase the possibilities for them to become rich and would probably raise their technical efficiency level. Moreover, for both groups of counties, the technical efficiency level has been reduced since 2002. The rate of technical change is high and is probably at the origin of this deterioration. Indeed, new technologies appear so fast that farmers do not have the time to assimilate them. Therefore, the solution to stop the deterioration of the technical efficiency level would consist in offering training relating to these technologies.

Several issues remain unexplored. In this study, we have examined the effect of urban proximity on technology, technical efficiency and technical change in the agricultural sector. Other components could be considered such as allocative efficiency, the study of which requires data on prices. We could also investigate if urban proximity affects rural poverty and inequalities.

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Appendix

Table A.1. : Definition of the variables

Variable	Definition	Unit
	Frontier variables	
Output	Gross output value of farming (deflated by the rural consumer price index)	Million yuan (constant prices)
Land	Cultivated area	1000 hectares
Labor	Agricultural labor	10,000 persons
Machinery	Total power of agricultural machinery	10000 kW
Chemical fertilizer	Consumption of chemical fertilizer	10,000 tons
	Class membership probability variables	
Geographical distance	Distance beetween a city and a county	Kilometers
City population	Total population at year-end	10,000 persons
City gdp	Gross domestic product (deflated by the urban consumer price index)	Yuan per person (constant prices)

Table A.2. : Descriptive statistics

	Obs	Mean	Std. Dev.	Min	Max
Output	702	11.15	8.16	0.05	46.08
Land	702	49.77	40.65	0.07	142.4
Labor	701	18.87	13.23	1.30	65.10
Machinery	702	43.08	36.18	2.51	223.04
Fertilizer	701	4.33	2.83	0.01	14.49
Proximity (GDP)	702	20.61	25.44	0	194.38
Proximity (population)	702	8.90	6.36	0	36.22

Note : output : million yuan (constant prices), land : 1000 hectares, labor : 10,000 persons, fertilizer 10,000 tons, machinery : 10000 kW.

Table A.3. : Divisions of administrative areas in China in 2002 and 2007

	Number of Regions at County Level	Number of Cities at County Level	Number of Districts under the Jurisdiction of Cities	Number of Rural counties
			2002	
National Total	2860	381	830	1649
Jiangsu	106	27	52	27
Zhejiang	88	22	30	36
Anhui	105	5	44	56
			2007	
National Total	2859	368	856	1635
Jiangsu	106	27	54	25
Zhejiang	90	22	32	36
Anhui	105	5	44	56

Note : data are from the China Statistical Yearbook (2003 and 2008).

Table A.4. : Specification tests for determining the number of regimes

Number of classes	Number of parameters	AIC	BIC	HQIC
1	12	0.437	0.515	0.467
2	26	-0.481	-0.312	-0.416
3	cannot be estimated	-	-	-

Note : the preferred specification has the lowest AIC, SBIC and HQIC. The model cannot be estimated when the number of groups specified is larger than the true number of groups; in this case, the model is overspecified (Orea and Kumbhakar, 2004).

Table A.5.a. : Proximity

	Counties close to urban centers	Remote counties
Proximity (population)	9.679	8.144
	(7.745)	(4.610)
Proximity (GDP)	24.036	17.234
	(31.945)	(16.658)

Notes : standard deviations in parenthesis

Table A.5.b. : T-test for difference between means for proximity

H0: Proximity in class 1 = Proximity in class 2. Ha: diff > 0		
	t	Pr(T > t)
Proximity (population)	1.306	0.097
Proximity (GDP)	1.448	0.075

Note : diff = mean(1) - mean(2)

Table A.6. : Wilcoxon test for difference between means for the efficiency scores

H0 : Efficiency in class 1 = Efficiency in class 2	
z	Prob > |z|
5.408	0.0000

Figure A.1. : Urban proximity ($WPOP$)